Aprendizaje profundo basado en la física

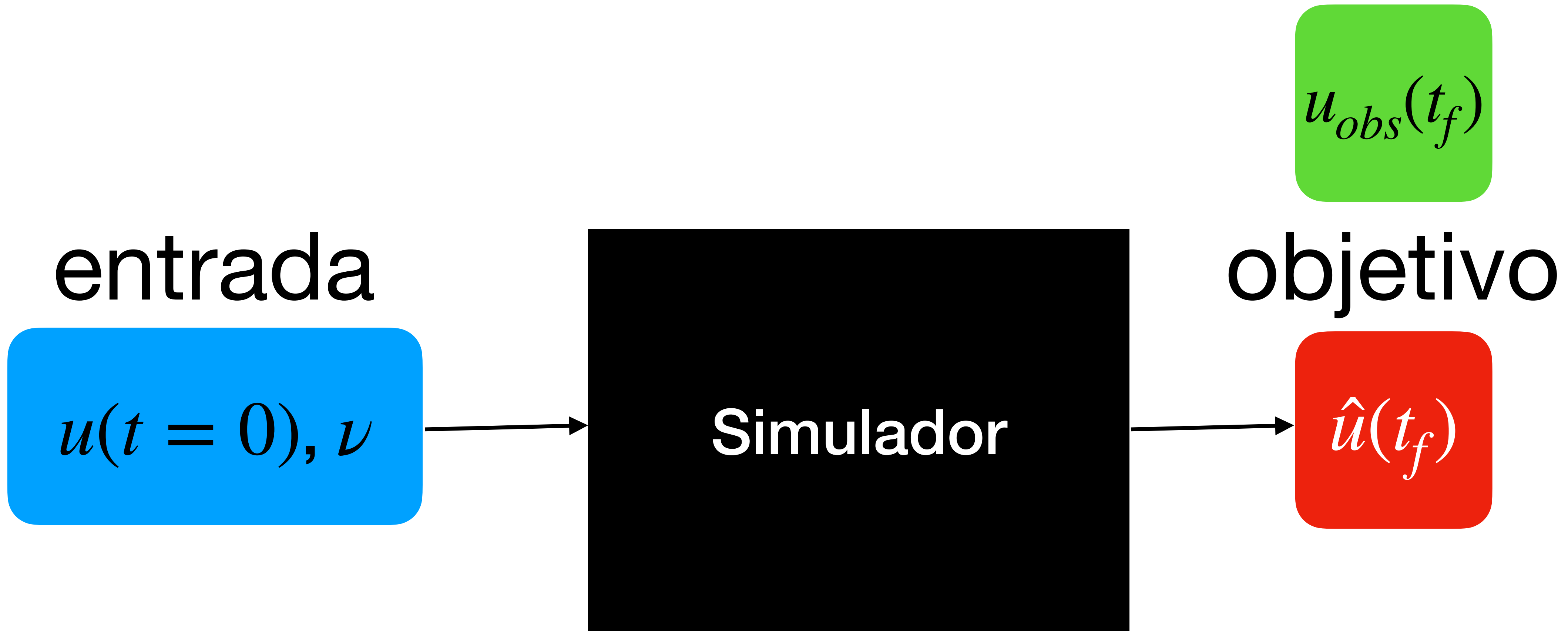
Semana 4: Embebiendo física dentro de redes neuronales

Docente: José I. Robledo - 28/04/2026

Física Diferenciadle

Differentiable Physics

- Contamos con un **simulador físico diferenciable**



¿Cómo debemos cambiar la entrada para mejorar el objetivo?

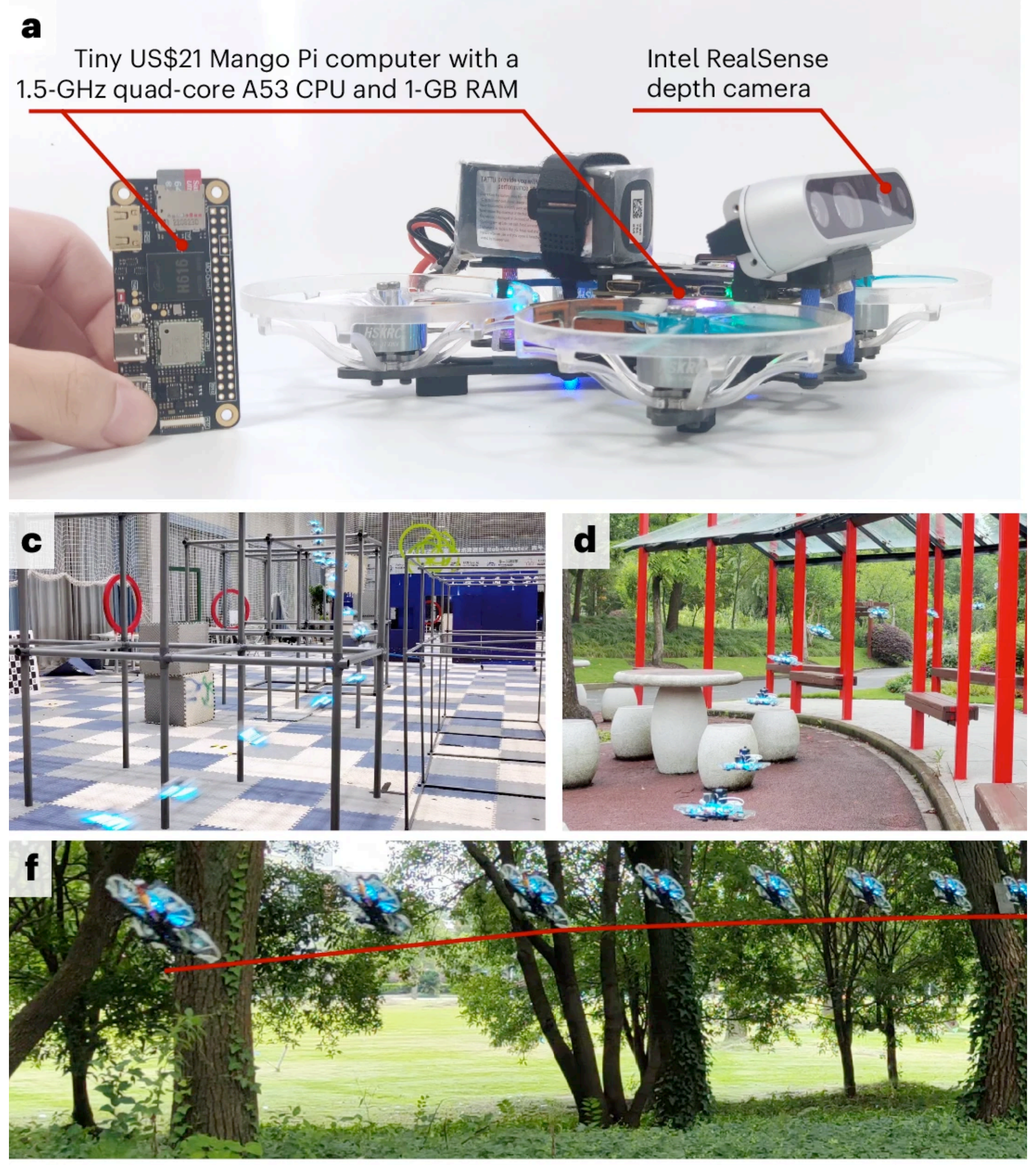
$$\hat{u}(t_f) = Simulador(u(t = 0), \nu)$$

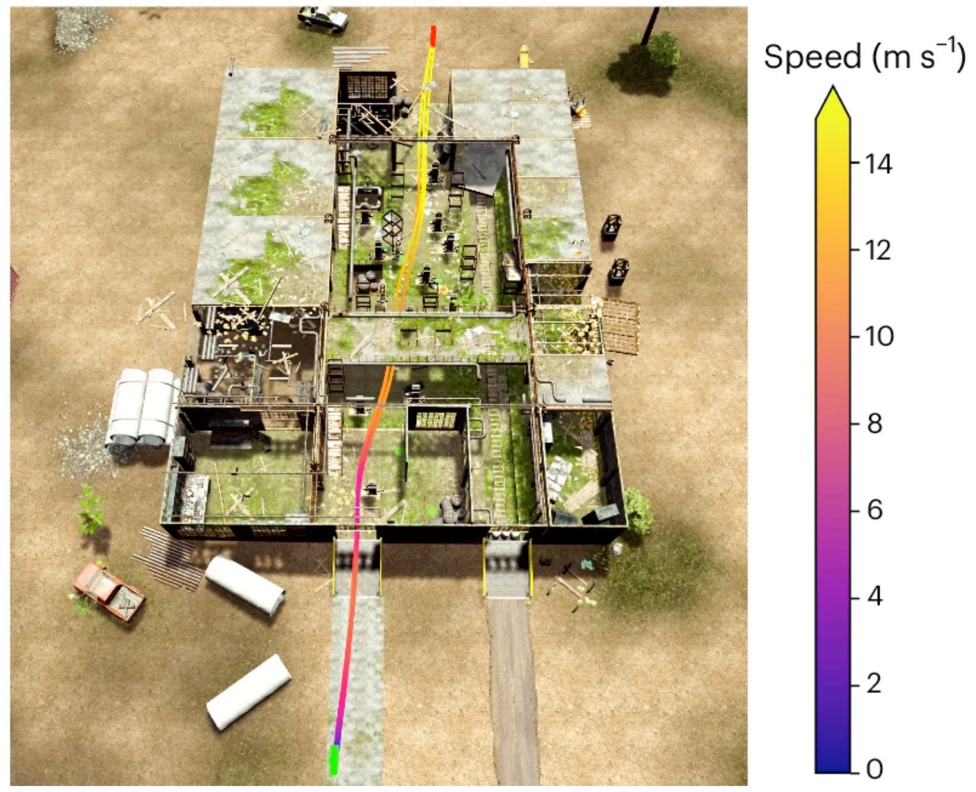
Aprovechamos PyTorch, JAX, TensorFlow

Aplicaciones

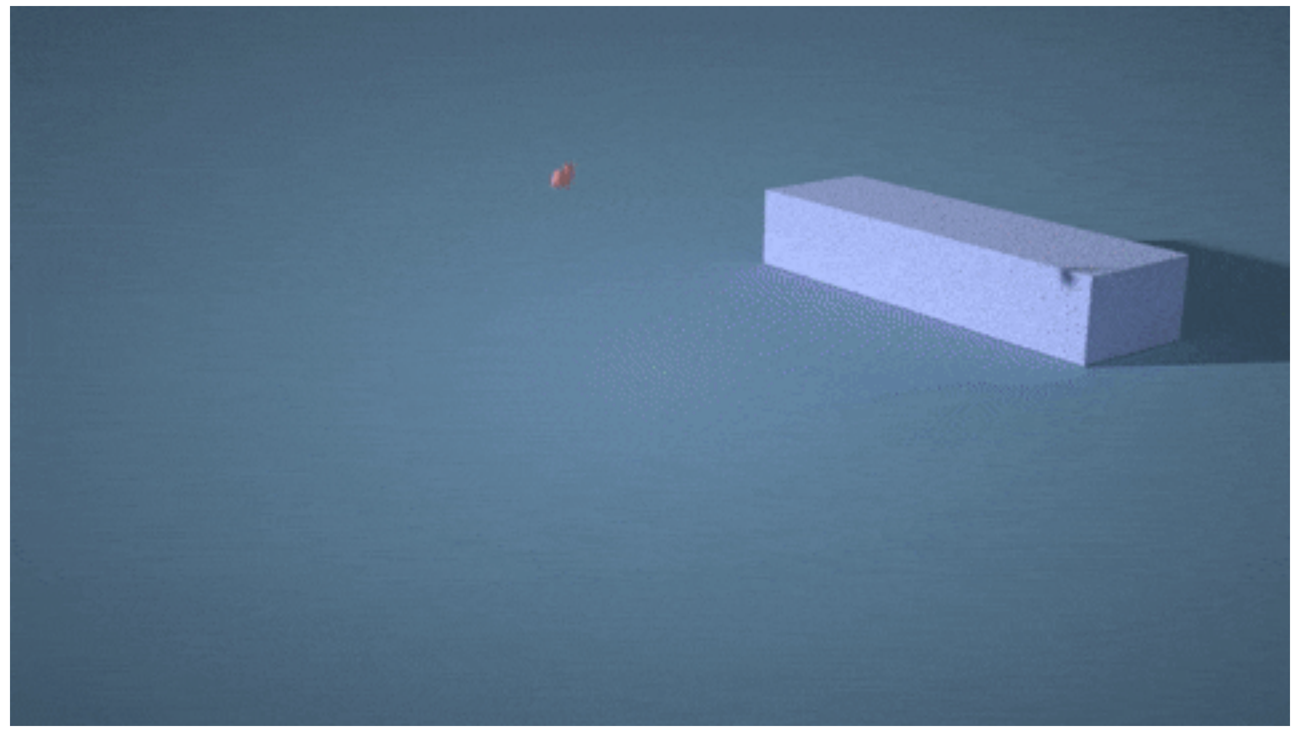
- Mecánica de fluídos
- Control robótico
- Termodinámica
- Física de plasma
- Óptica de ondas diferenciadle (TorchOptics)

Learning vision-based agile flight via differentiable physics

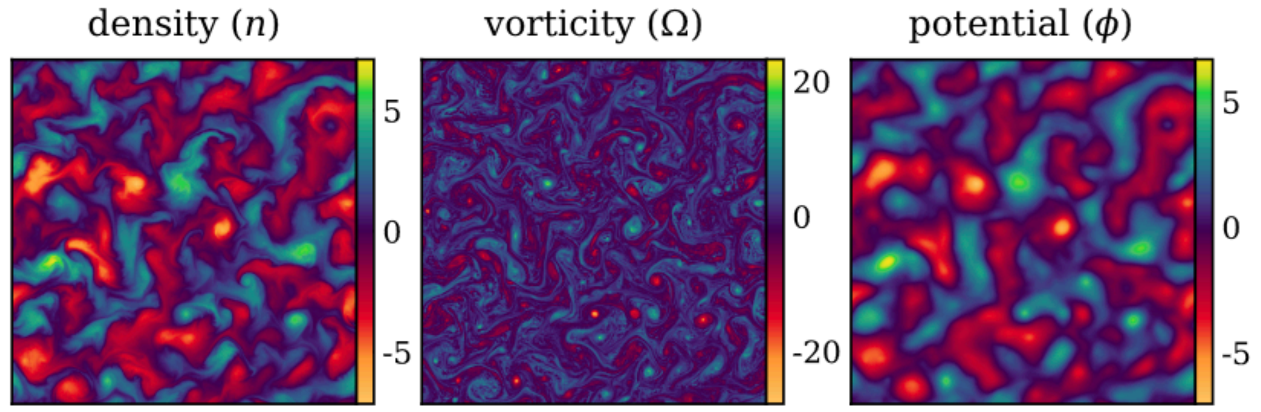




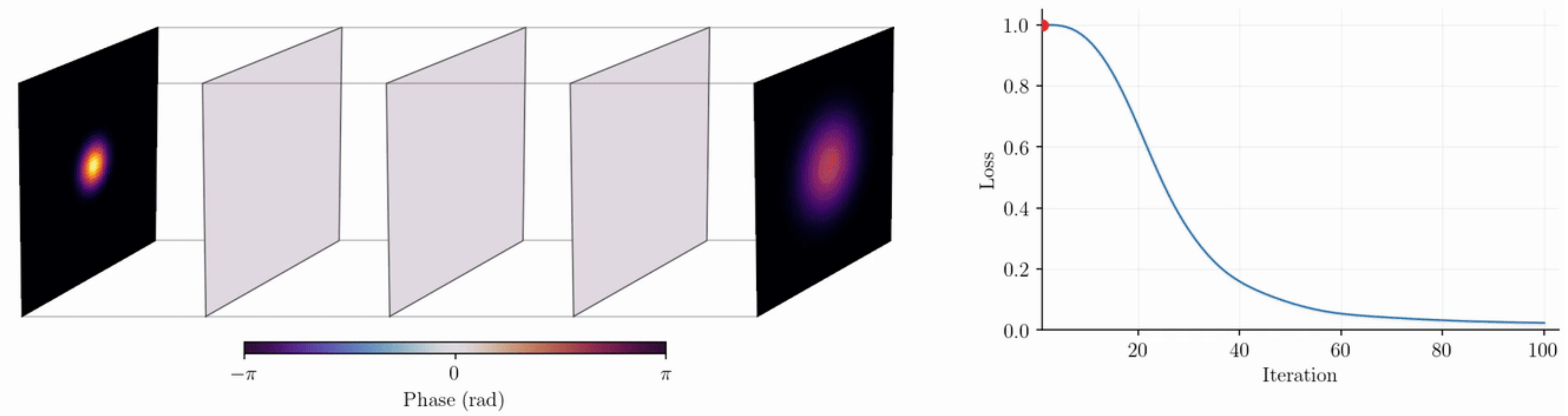
https://www.taichi-lang.org/



Learning via Differentiable Physics for Plasma Turbulence



Train a diffractive optical system to convert a Gaussian beam into a petal beam



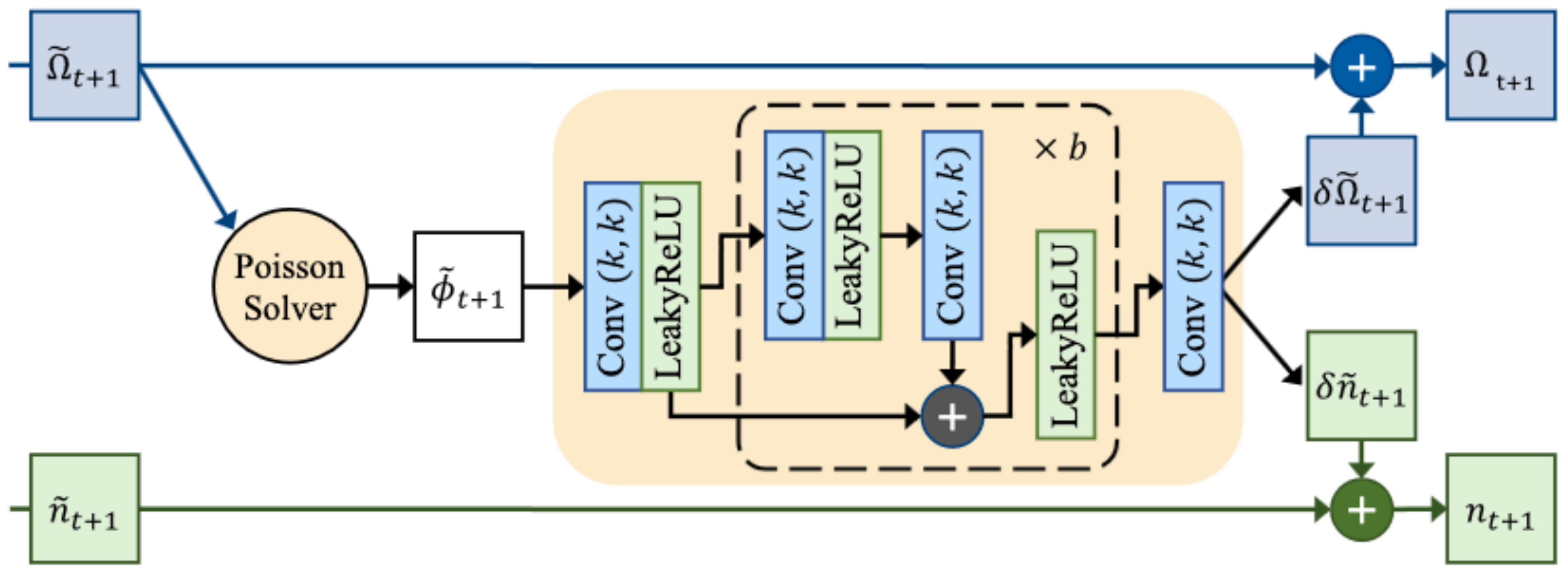
Física Diferenciable

Differentiable Physics

- **Física Diferenciable** extiende simuladores físicos tradicionales, permitiendo utilizar Autograd para calcular los gradientes del simulador

$$\frac{\partial u(t)}{\partial u_0}, \text{ donde } u_0 = u(t = 0)$$

$$\frac{\partial u(t)}{\partial \nu}, \ \nu \text{ parámetros físicos}$$



- Integra la simulación entera dentro del proceso del aprendizaje!

Física Diferenciadle

Differentiable Physics

- Necesitamos una formulación continua del proceso físico que nos interesa, $\mathcal{P}^*(\vec{u}, \nu)$, con $\vec{u}(\vec{u}, t) : \mathbb{R}^d \times \mathbb{R}^+ \to \mathbb{R}^d$.

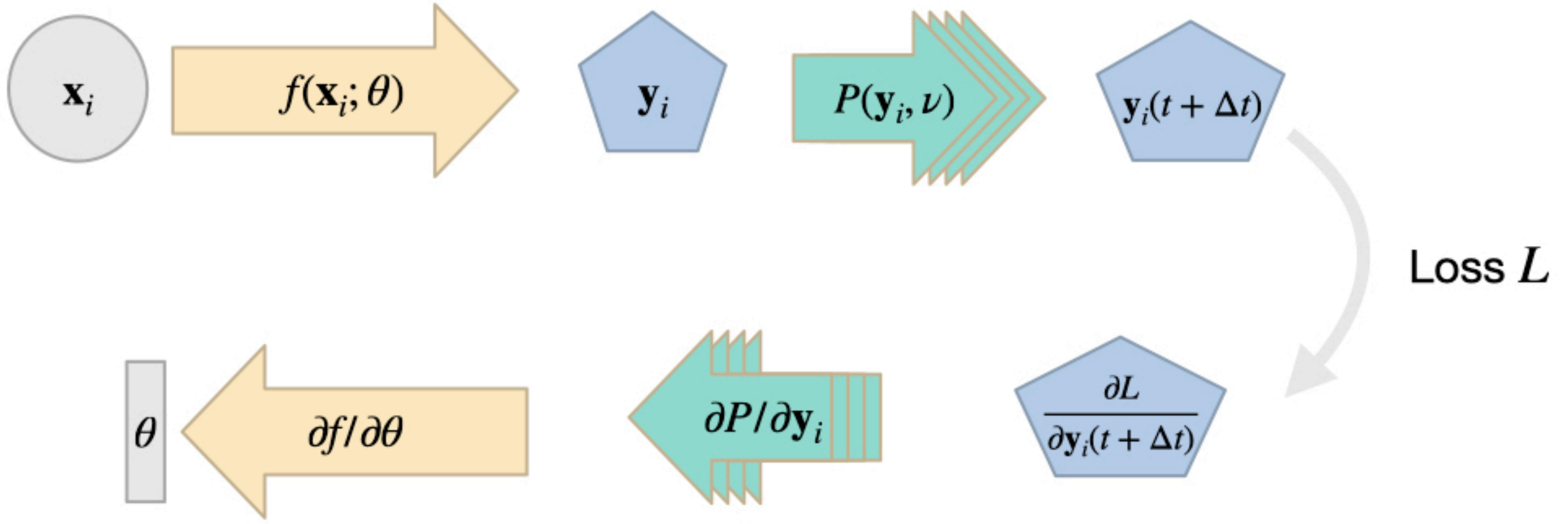
- Discretizando el proceso en Δt, definimos $\mathcal{P} \approx \mathcal{P}^*$, tal que $\vec{u}(t + \Delta t) = \mathcal{P}(\vec{u}(t), \nu) = \mathcal{P}_m \circ \cdots \circ \mathcal{P}_1(\vec{u}(t), \nu)$

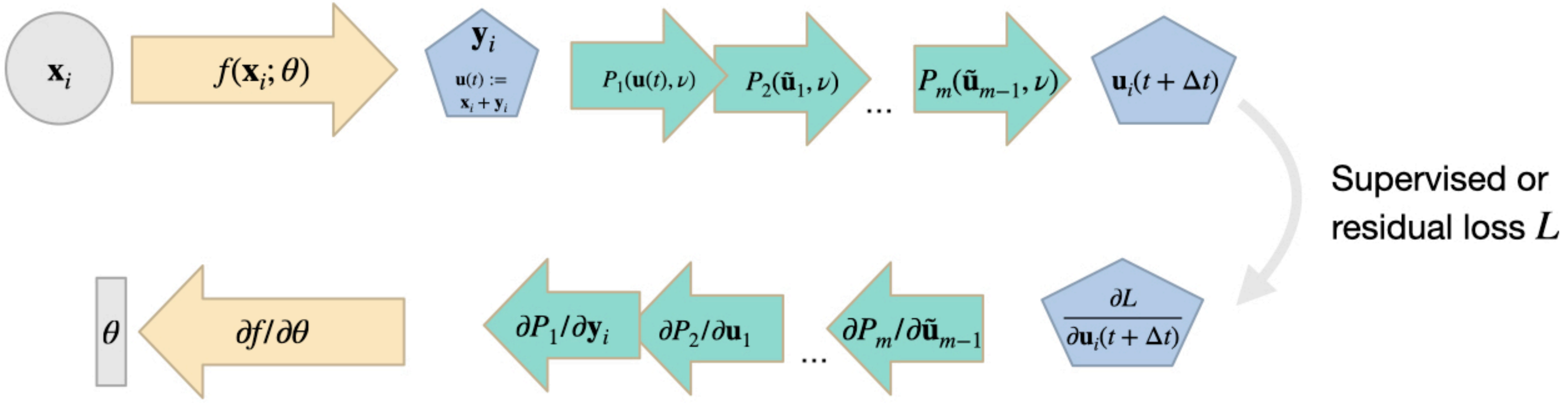
Operadores monolíticos

- $$\frac{\partial l}{\partial \mathbf{u}}\bigg|_{\mathbf{u}^n} = \frac{\partial \mathcal{P}_2}{\partial \mathbf{z}}\bigg|_{\mathbf{z}=\mathcal{P}_1(\mathbf{u}^n)} \frac{\partial \mathcal{P}_1}{\partial \mathbf{u}}\bigg|_{\mathbf{u}=\mathbf{u}^n}, \qquad \mathbf{z} = \mathcal{P}_1(\mathbf{u})$$

Física Diferenciable

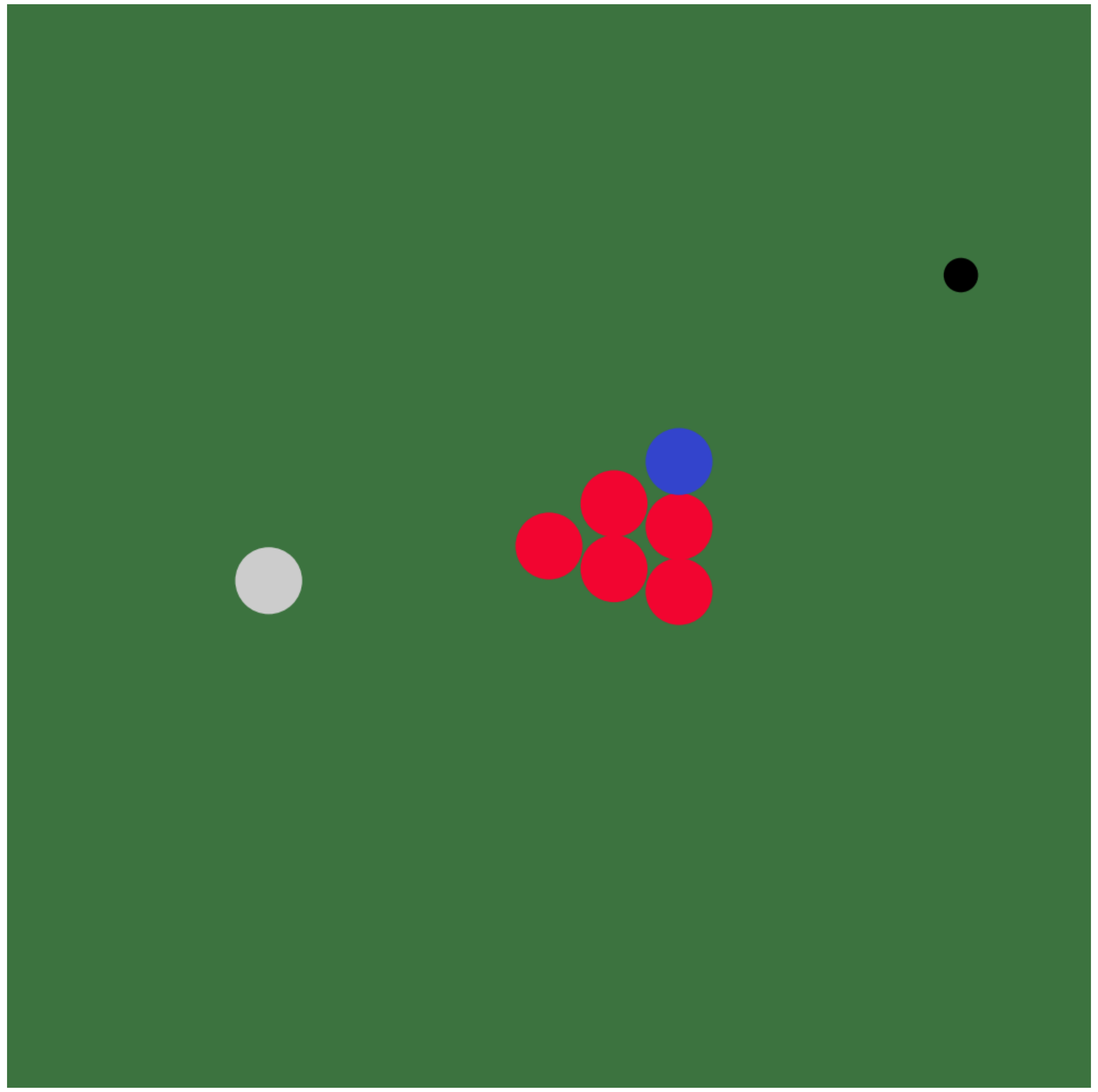
Differentiable Physics

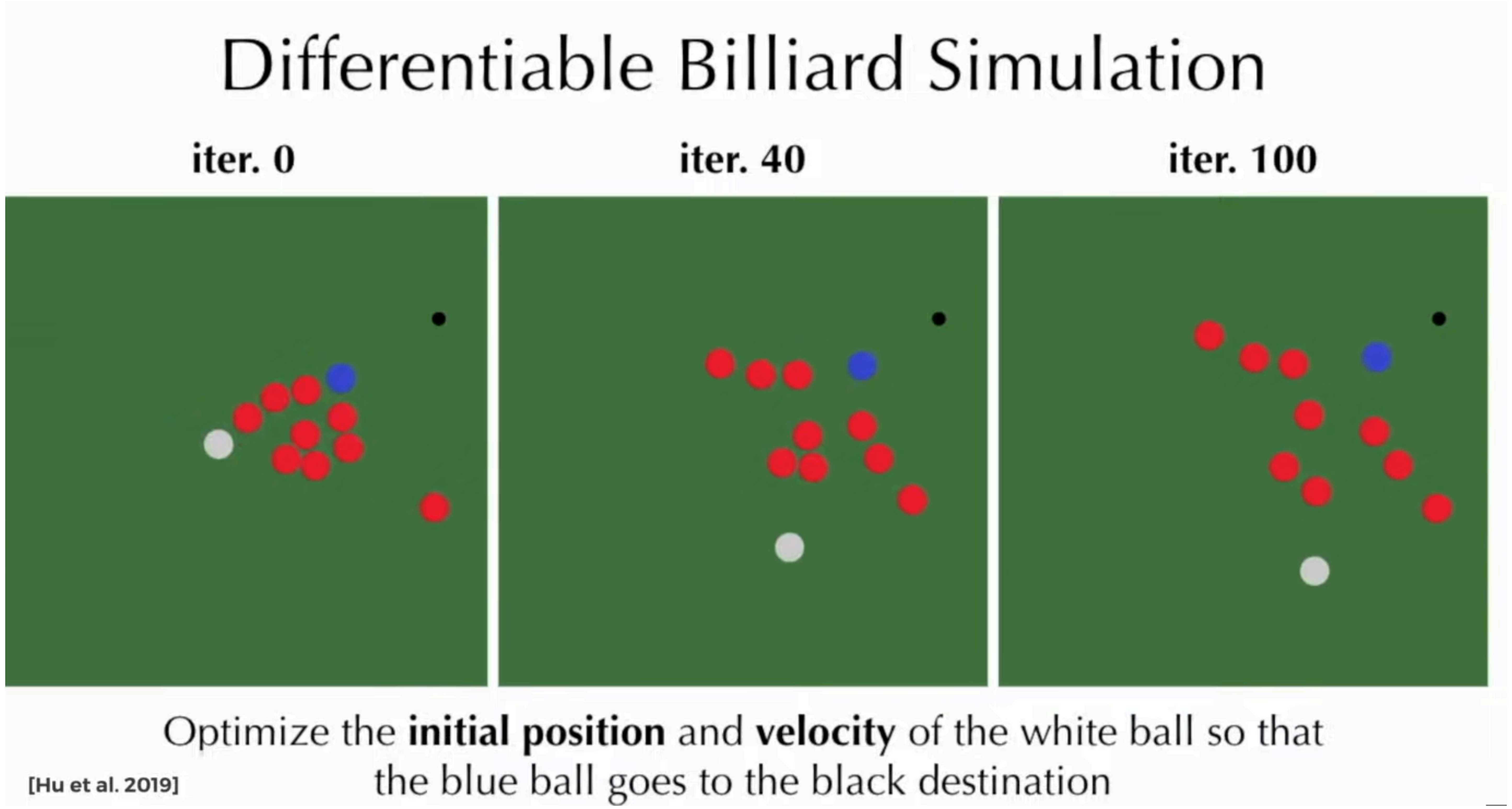




Entender Física Diferenciable

Ejemplo: billar





Notebook billar

NN + FD

Solver in the loop

El simulador no es suficiente por si solo

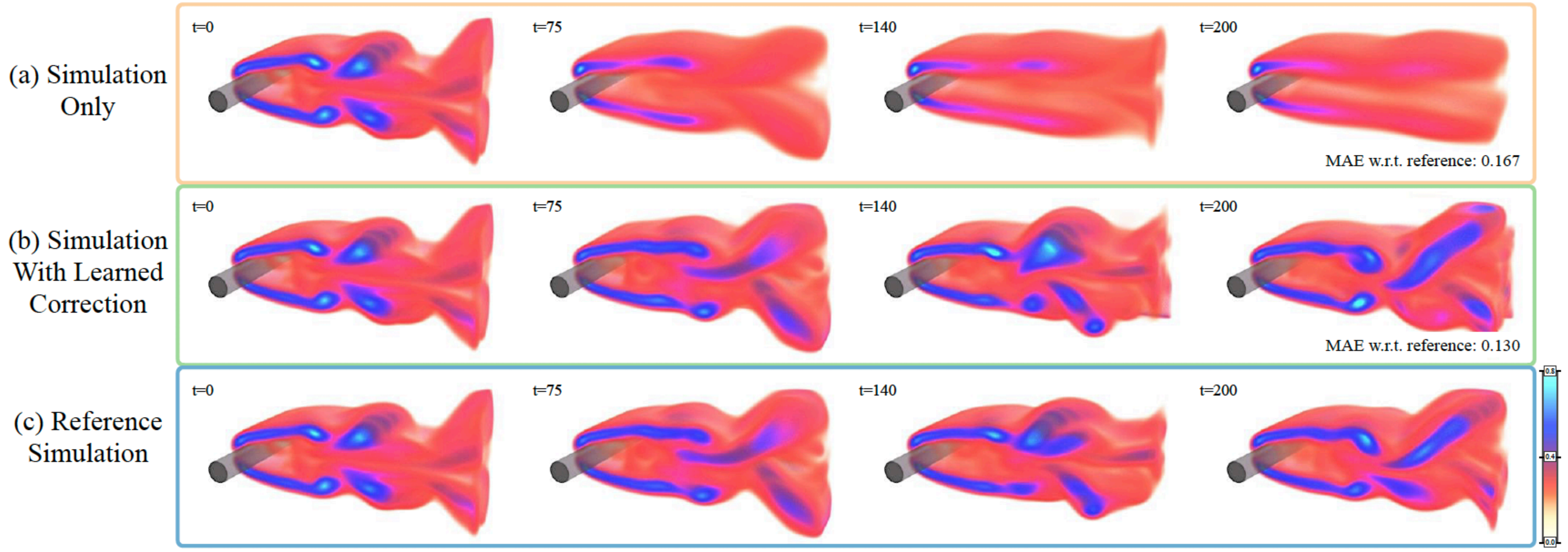
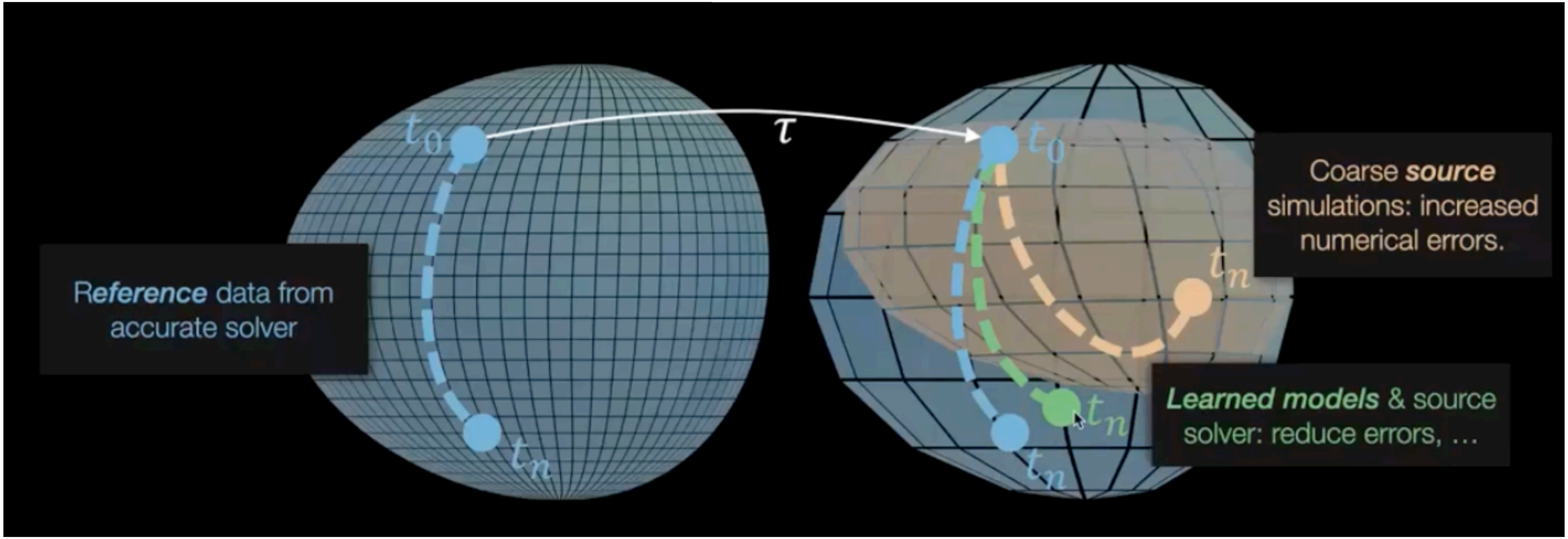


Figure 1: A 3D fluid problem (shown in terms of vorticity) for which the regular simulation introduces numerical errors that deteriorate the resolved dynamics (a). Combining the same solver with a learned corrector trained via differentiable physics (b) significantly reduces errors w.r.t. the reference (c).



https://arxiv.org/abs/2007.00016

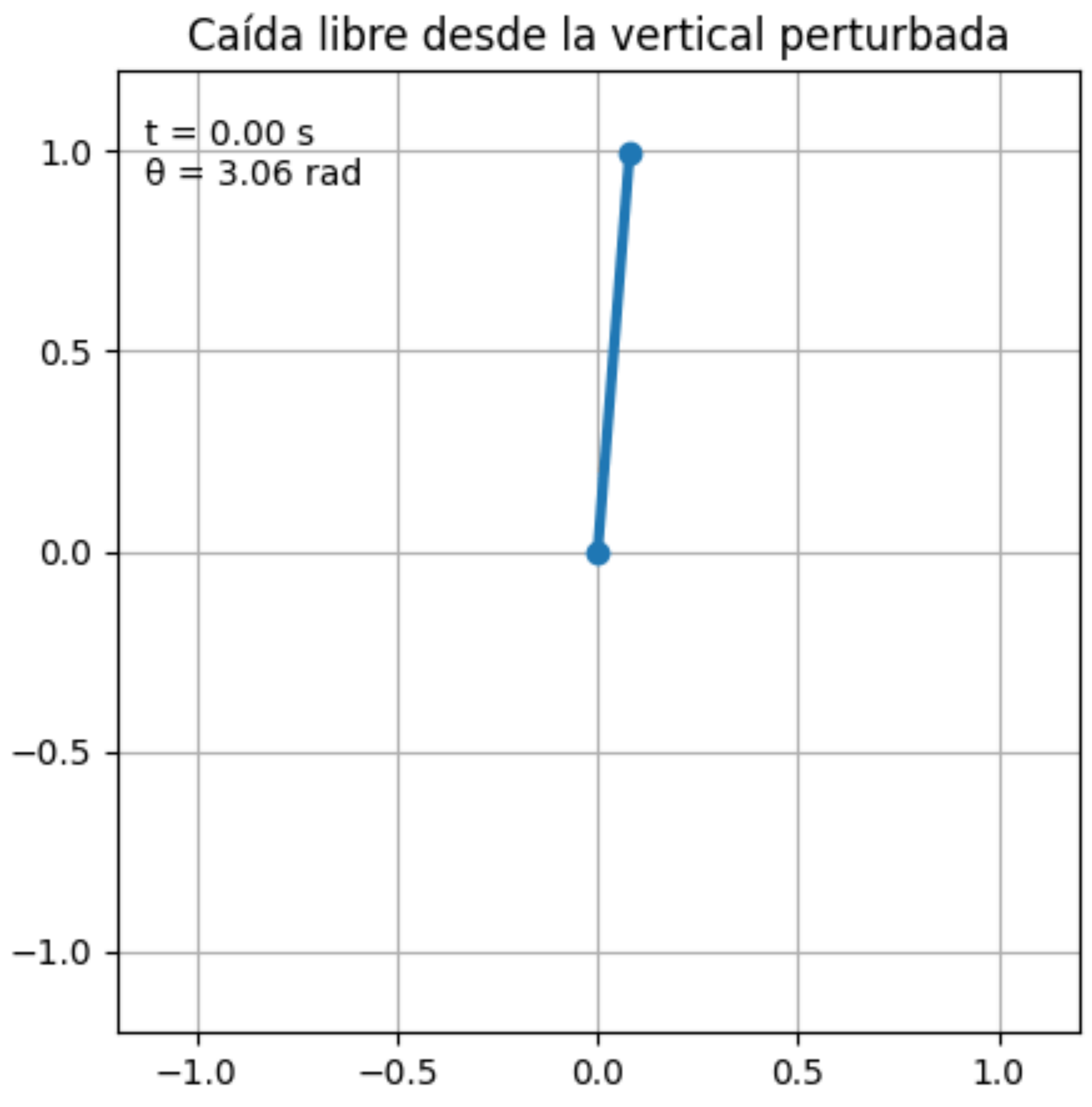
Ejemplo Péndulo

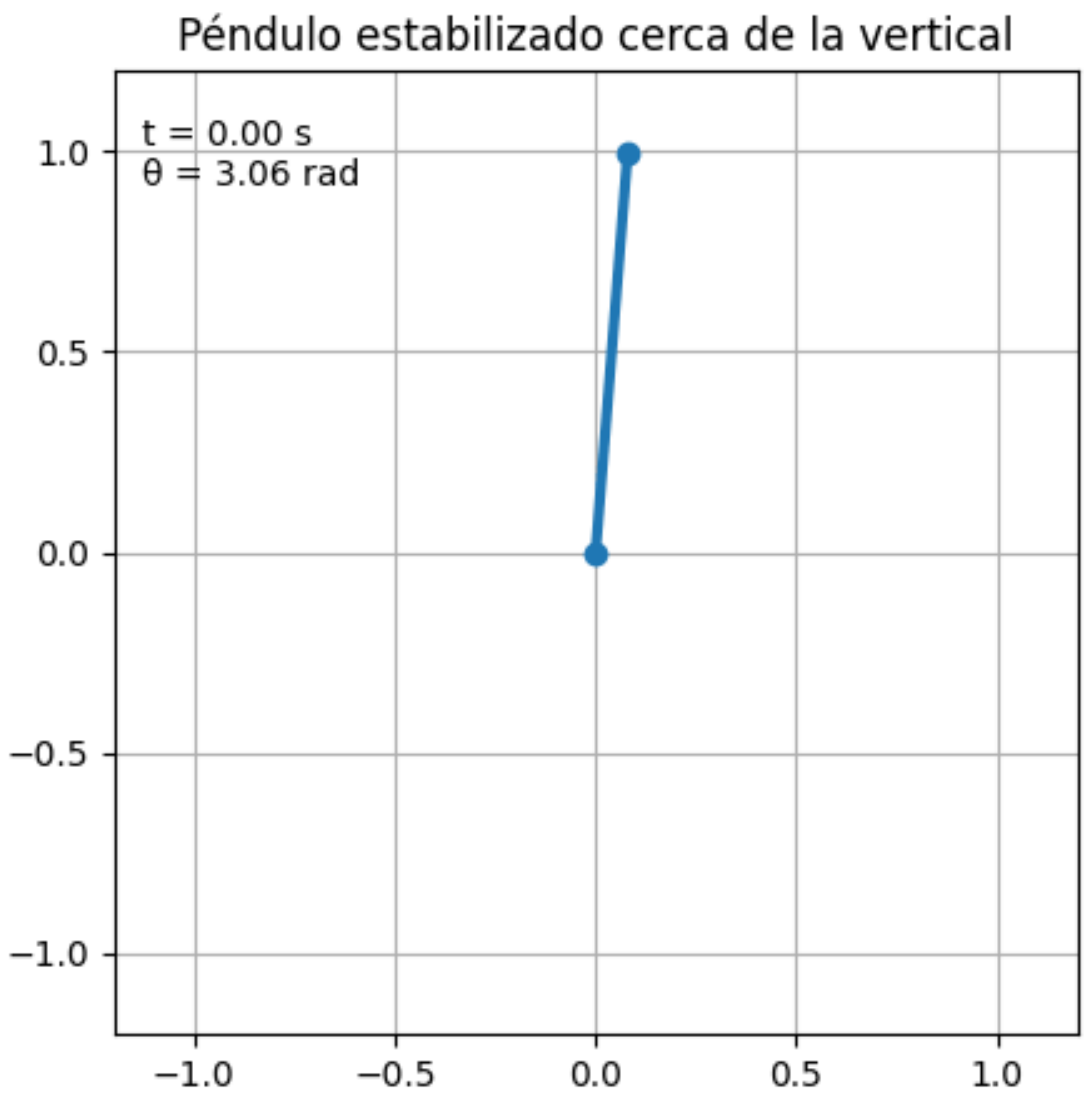
Física diferenciable para Control

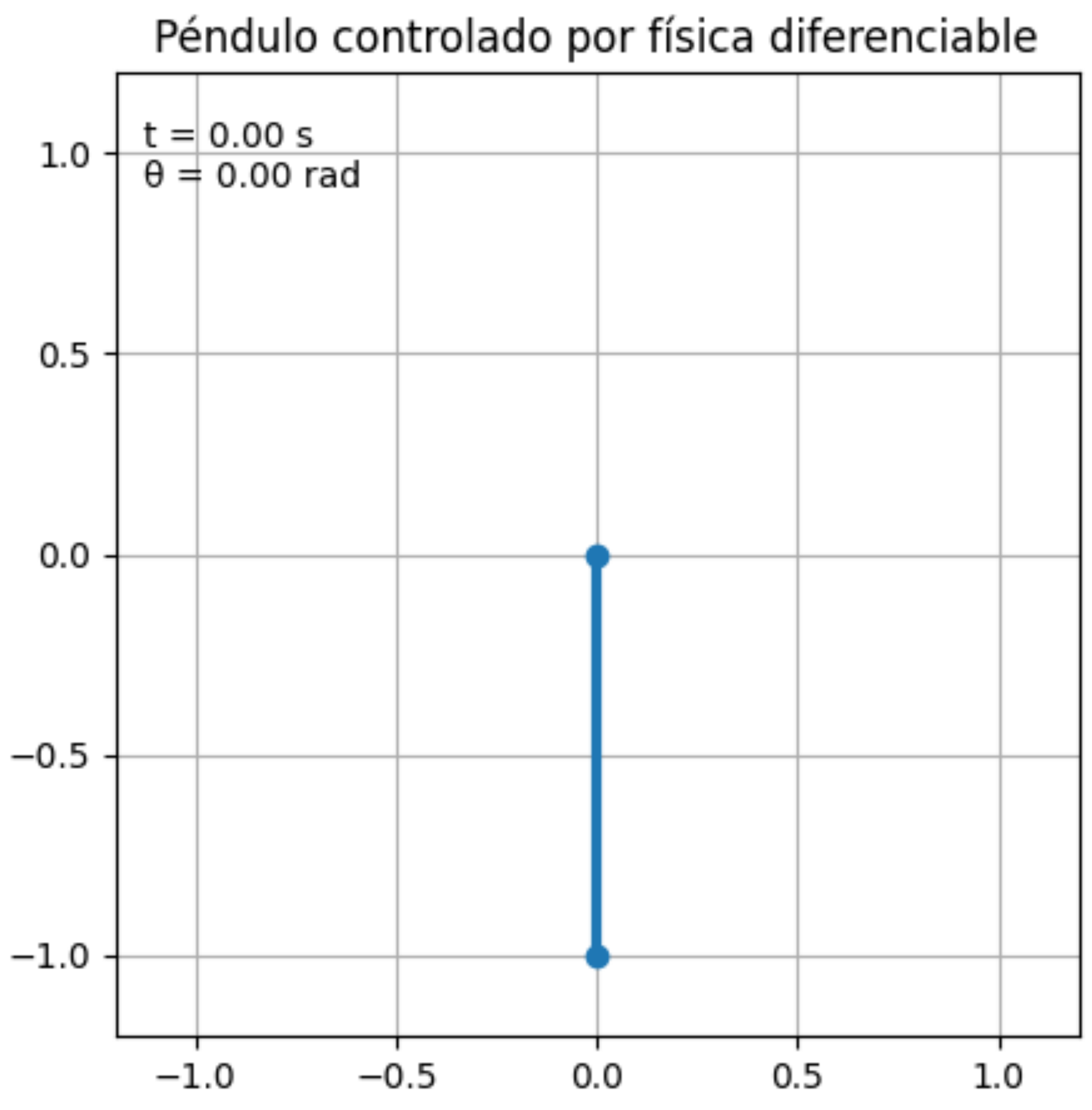
$$\dot{\theta} = \omega$$

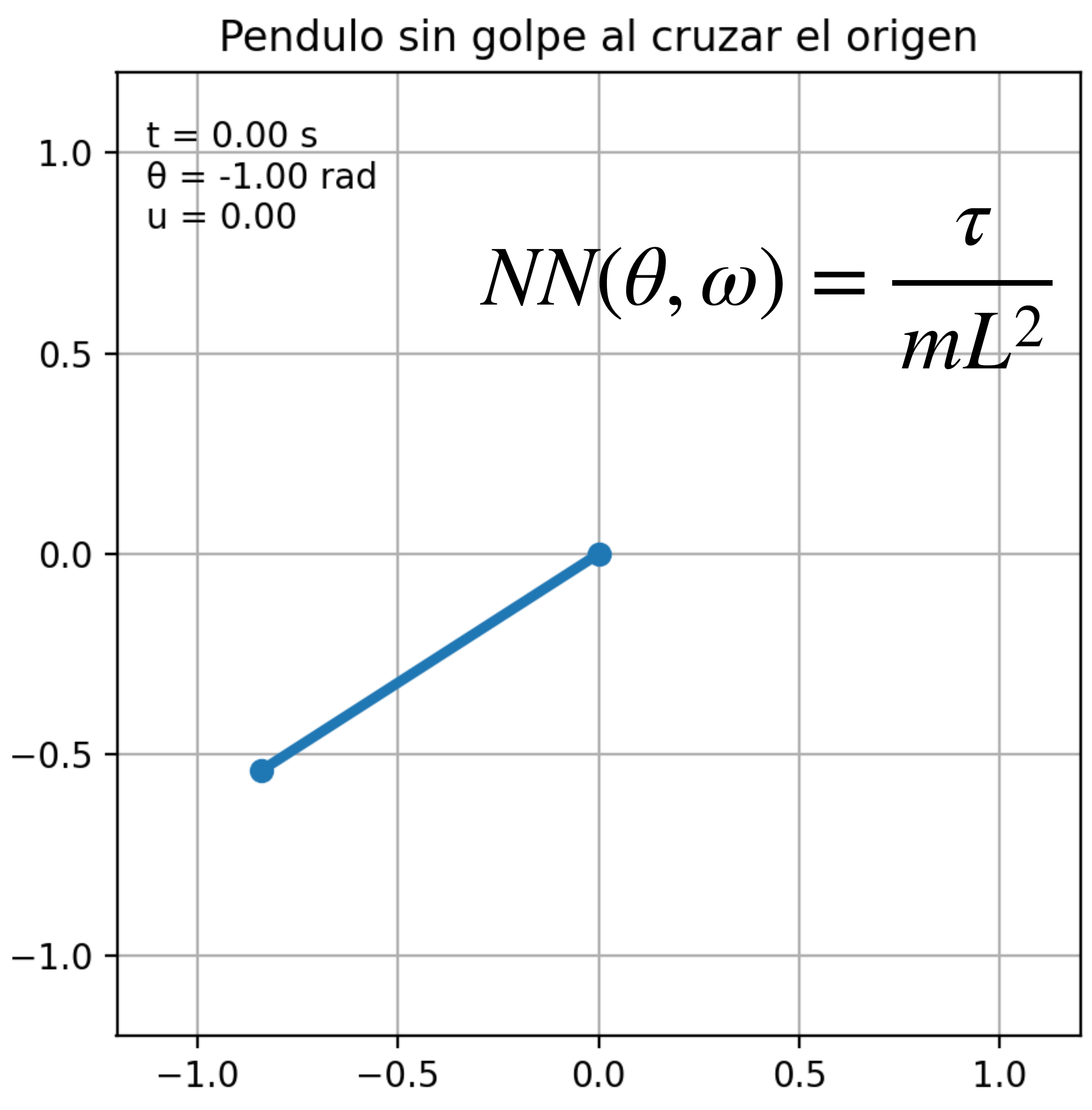
$$\dot{\omega} = -\frac{g}{L}\sin(\theta) - b\,\omega + \frac{\tau}{mL^2},$$

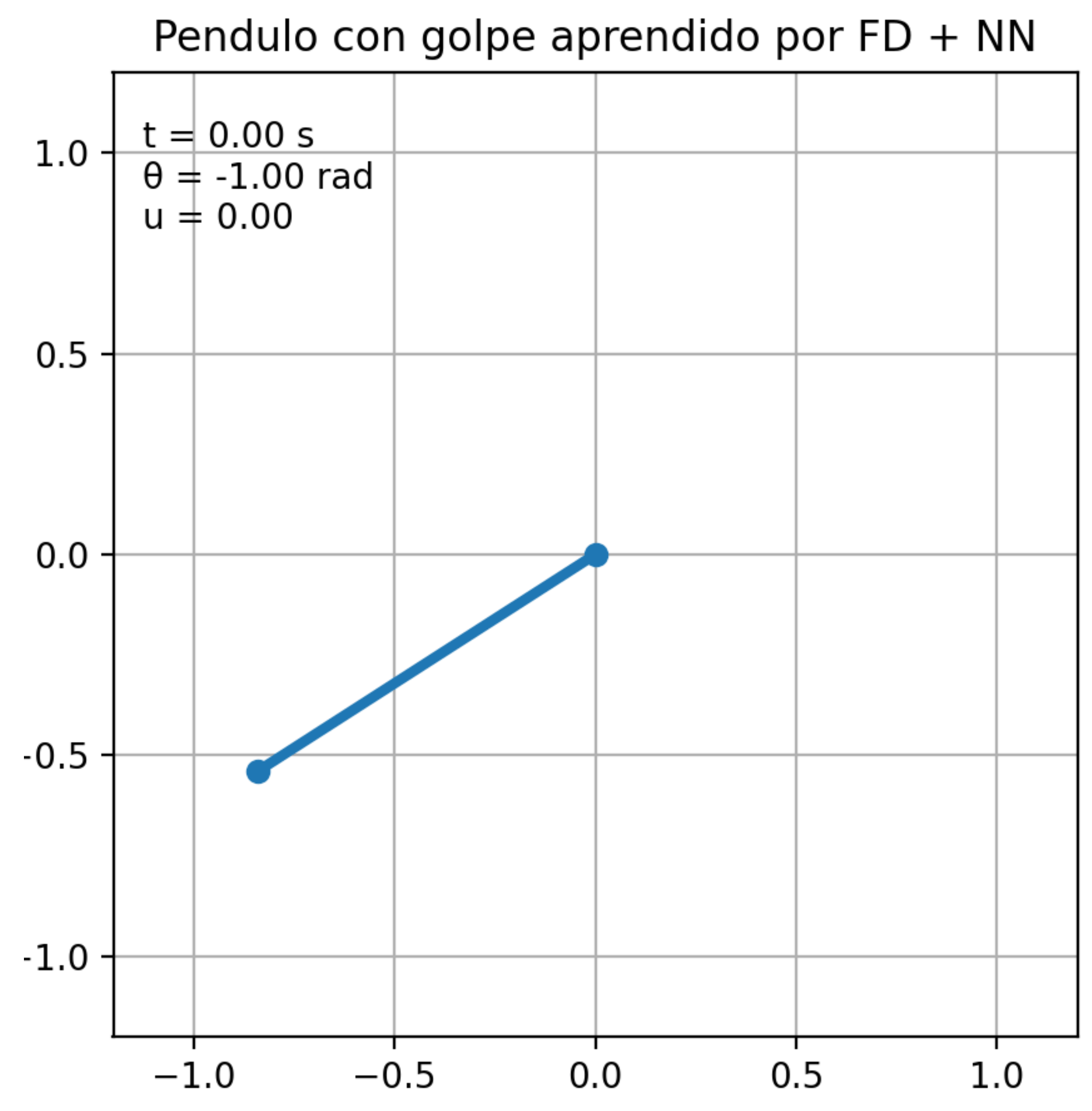
gravedad Amort. Torque ext.











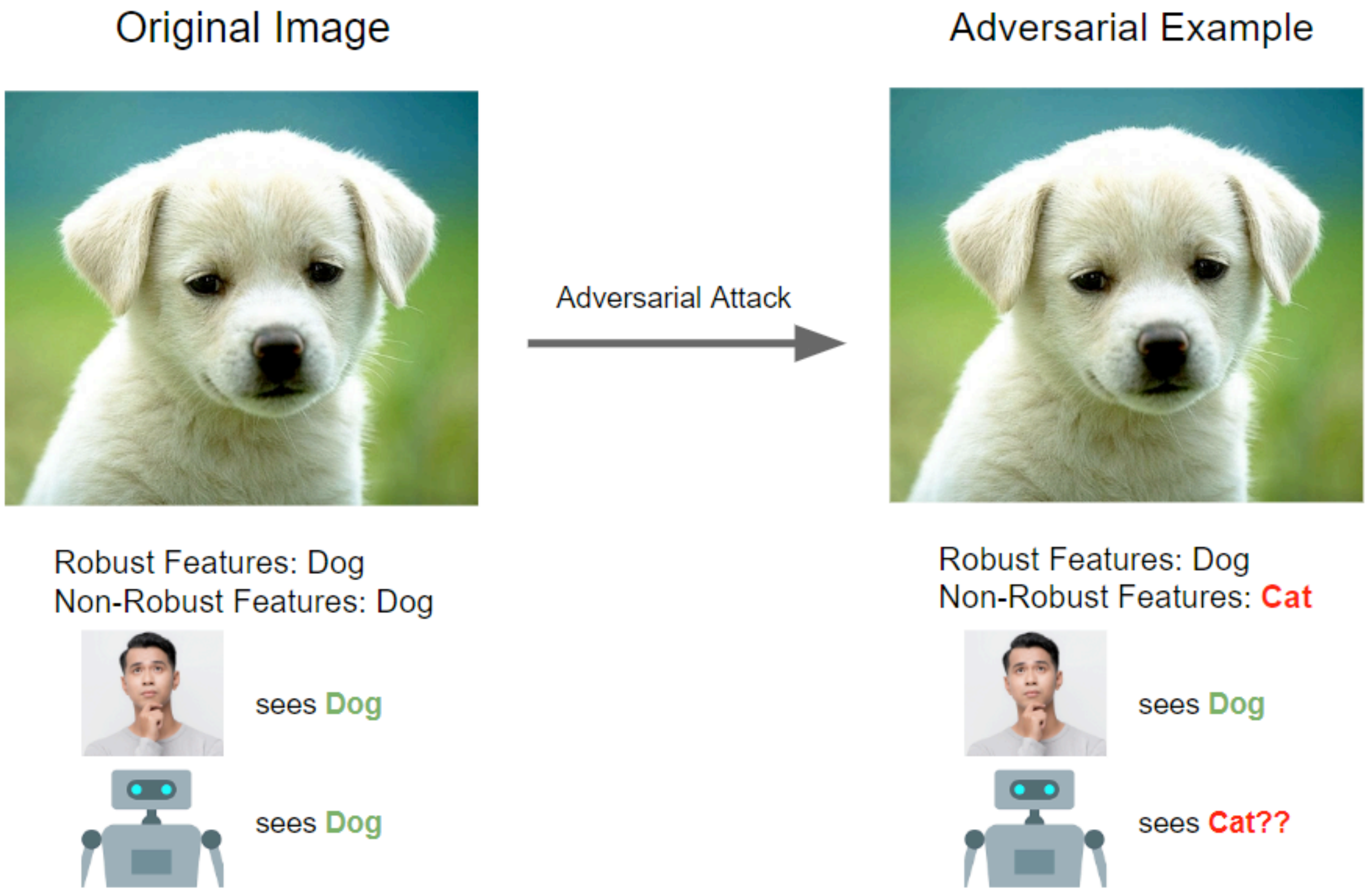
Ejemplo Péndulo

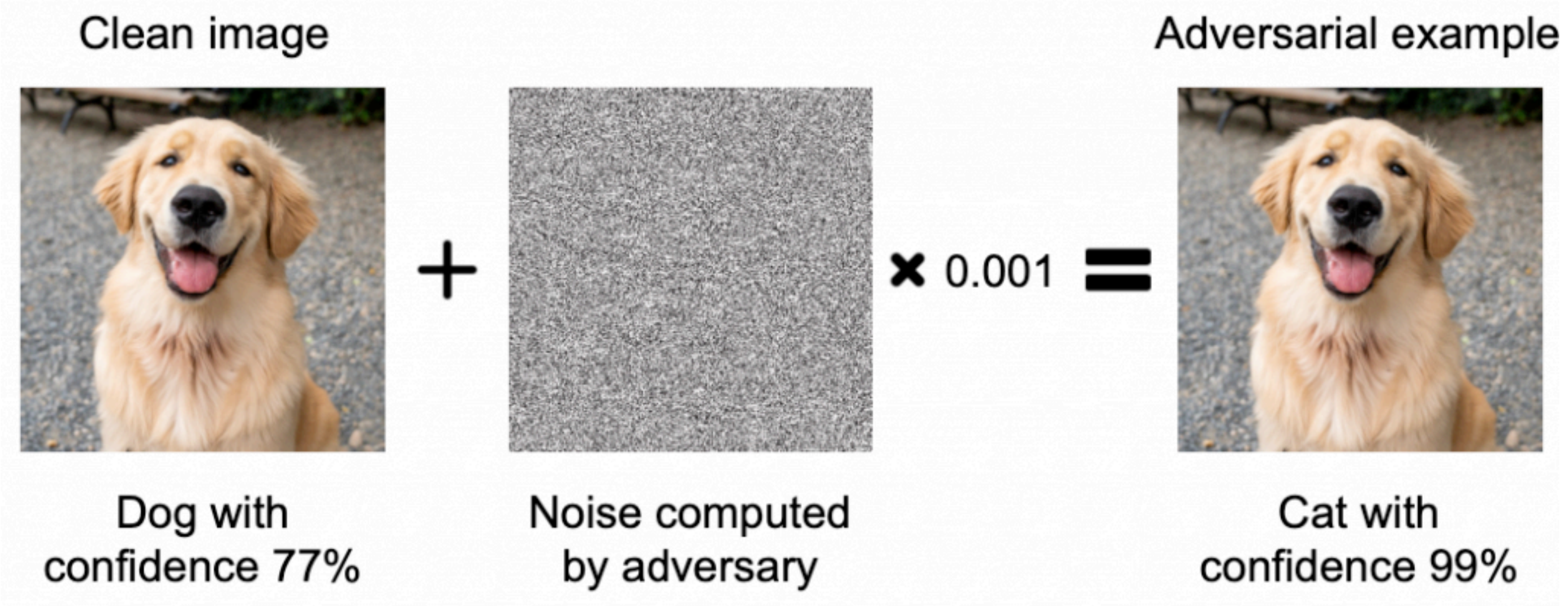
Física diferenciable para Control

Notebook control péndulo

Ejemplo ataque adversarial

Engañando a las redes neuronales





Ejemplo ataque adversario

Engañando a las redes neuronales

Podemos pensar a la NN como una caja negra diferenciable respecto a las variables de entrada!

entrada

NN

$$\begin{pmatrix} 0.71 \\ 0.14 \\ 0.11 \\ 0.04 \end{pmatrix} \begin{matrix} \text{Perro} \\ \text{Lobo} \\ \text{Oso} \\ \text{Gato} \end{matrix}$$

$\mathbf{X}_{256\times 256}$ $\quad$ w **fijo** $\quad$ a

Nos interesa $\dfrac{\partial a_{gato}}{\partial \mathbf{X}}$

Notebook ataque adversario